Information Retrieval

Evaluation in IR systems

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Why System Evaluation?

- There are many retrieval models/ algorithms/ systems, which one is the best?
- What is the best component for:
 - Ranking function (dot-product, cosine, ...)
 - Term selection (stopword removal, stemming...)
 - Term weighting (TF, TF-IDF,...)

Difficulties in Evaluating IR Systems

- Effectiveness is related to the *relevancy* of retrieved items.
- Relevancy is not typically binary but continuous.
- Even if relevancy is binary, it can be a difficult judgment to make.
- Relevancy, from a human standpoint, is:
 - Subjective: Depends upon a specific user's judgment.
 - Situational: Relates to user's current needs.
 - Cognitive: Depends on human perception and behavior.
 - Dynamic: Changes over time.

Human Labeled Corpora (Gold Standard)

• Start with a corpus of documents.



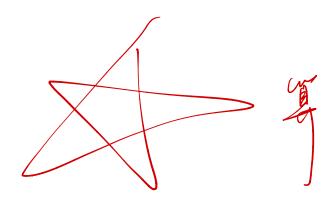
- Collect a set of queries for this corpus.
- Have one or more human experts exhaustively label the relevant documents for each query.
- Typically assumes binary relevance judgments.
- Requires considerable human effort for large document/query corpora.

Standard Collections

TABLE 4.3 Common Test Corpora

Collection	NDocs	NQrys	Size (MB)	Term/Doc	Q-D RelAss
ADI	82	35			
AIT	2109	14	2	400	>10,000
CACM	3204	64	2	24.5	
CISI	1460	112	2	46.5	
Cranfield	1400	225	2	53.1	
LISA	5872	35	3		
Medline	1033	30	1		
NPL	11,429	93	3		
oshmed	34,8566	106	400	250	16,140
Reuters	21,578	672	28	131	
TREC	740,000	200	2000	89-3543	» 100,000

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EVALUATING UNRANKED RESULTS

Precision and Recall

- 个 查準率
- **Precision** fraction of retrieved docs that are relevant = P(relevant | retrieved) 抓身少国来有多少相關
- **Recall**: fraction of relevant docs that are retrieved =

 (P(retrieved | relevant) 針對重約有多少排開 分母 找到有多少分子

 all mum 可 clated docs

a+C

	Relevant	Nonrelevant
Retrieved	tp 🔼	fp b
Not Retrieved	fn C	tn 👃

Entire

document

collection

Relevant Retrieved documents

Recall 重要: 法條前菜檢索 專利檢案

Precision and Recall

- Precision: fraction of retrieved docs that are relevant = P(relevant|retrieved)
- Recall: fraction of relevant docs that are retrieved = P(retrieved|relevant)

	Relevant	Nonrelevant
Retrieved	tp	fp
Not Retrieved	fn	tn

- Precision P = tp/(tp + fp)
- Recall R = tp/(tp + fn)
- Accuracy A = (tp+tn)/(tp+fp+fn+tn)

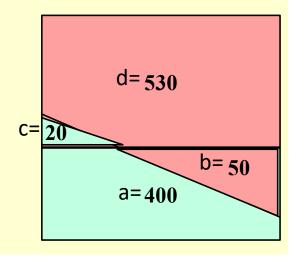
Precision, Recall, Accuracy

Actual Test Cases:

550 "+"

450 "-"

Predicted:



For this:

$$a = 400$$

$$b = 50$$

$$c = 20$$

$$d = 530$$

Precision =
$$d / (b + d) = 530 / 580 = 91.4\%$$

Recall =
$$d / (c + d) = 530 / 550 = 96.4\%$$

Accuracy =
$$(a+d)/(a+b+c+d)$$

= $(530+400)/(530+20+50+400) = 93\%$

Should we instead use the accuracy measure for evaluation?

- Given a query, an engine classifies each doc as "Relevant" or "Nonrelevant"
- The accuracy of an engine: the fraction of these classifications that are correct
- Accuracy is a commonly used evaluation measure in machine learning classification work but not in IR
- Why is this not a very useful evaluation measure in IR?

Why not just use accuracy?

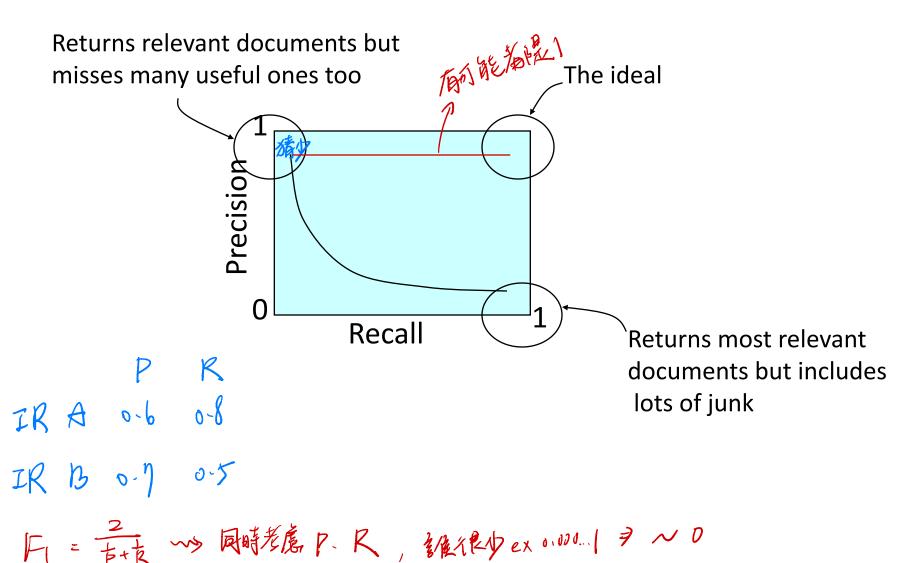
fir IR、不會用 accuracy

• How to build a 99.9999% accurate search engine on a low budget.... 沒有相關的文章 上面的 条統都不同答

Snoogle.com	
Search for:	
0 matching results found.	

 People doing information retrieval want to find something and have a certain tolerance for junk.

Trade-off between Recall and Precision



F-Measure

	relevant	not relevant	
retrieved	20	40	60
not retrieved	60	1,000,000	1,000,060
	80	1,000,040	1,000,120

$$P = 20/(20 + 40) = 1/3$$

$$\blacksquare$$
 $R = 20/(20 + 60) = 1/4$

$$F_1 = 2 / (1/P + 1/R) = 2/7$$

F-Measure

- One measure of performance that takes into account both recall and precision.
- Harmonic mean of recall and precision:

$$F = \frac{2PR}{P+R} = \frac{2}{\frac{1}{R} + \frac{1}{P}}$$

• Compared to arithmetic mean, both need to be high for harmonic mean to be high.

E Measure (parameterized F Measure)

 A variant of F measure that allows weighting emphasis on precision over recall:

$$E = \frac{(1+\beta^2)PR}{\beta^2 P + R} = \frac{(1+\beta^2)}{\frac{\beta^2}{R} + \frac{1}{P}}$$

- Value of β controls trade-off:
 - $-\beta$ = 1: Equally weight precision and recall (E=F).
 - $-\beta > 1$: Weight recall more.
 - $-\beta$ < 1: Weight precision more.

EVALUATING RANKED RESULTS

Evaluating ranked results

- Evaluation of ranked results:
 - The system can return any number of results
 - By taking various numbers of the top returned documents (levels of recall), the evaluator can produce a precision-recall curve

Computing Recall/Precision Points

- For a given query, produce the ranked list of retrievals.
- Adjusting a threshold on this ranked list produces different sets of retrieved documents, and therefore different recall/precision measures.
- Mark each document in the ranked list that is relevant according to the gold standard.
- Compute a recall/precision pair for each position in the ranked list that contains a relevant document.

Computing Recall/Precision Points:

Example 1

n	doc#	relevant
1	588	Х
2	589	X
3	576	
4	590	X
5	986	
6	592	X
7	984	
8	988	
9	578	
10	985	
11	103	
12	591	
13	772	X
14	990	Х

Let total # of relevant docs = 6

Check each new recall point:

R=5/6=0.833; p=5/13=0.38

Computing Recall/Precision Points: Example 2

n	doc#	relevant	Let total # of relevant docs = 6
1	588	Х	Check each new recall point:
2	576		
3	589	X	R=1/6=0.167; P=1/1=1
4	342		(
5	590	X	R=2/6=0.333; P=2/3=0.667
6	717		2/ ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° °
7	984		R=3/6=0.5; P=3/5=0.6
8	772	X	
9	321	X	R=4/6=0.667; P=4/8=0.5
10	498		D_F/C_0 933, D_F/0_0 FFC
11	113		R=5/6=0.833; P=5/9=0.556
12	628		
13	772		D C/C 1 0 C/14 0 420
14	592	X	R=6/6=1.0; p=6/14=0.429

Interpolating a Recall/Precision Curve

 Interpolate a precision value for each standard recall level:

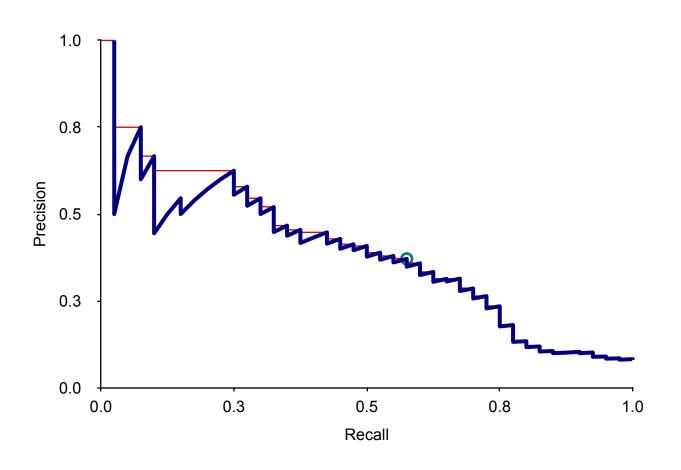
$$- r_j \in \{0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$$

$$- r_0 = 0.0, r_1 = 0.1, ..., r_{10} = 1.0$$

• The interpolated precision at the *j*-th standard recall level is the maximum known precision at any recall level between the *j*-th and (*j* + 1)-th level:

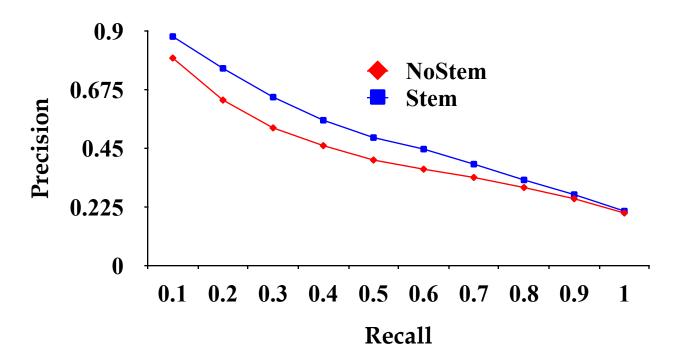
$$P(r_j) = \max_{r_j \le r \le r_{j+1}} P(r)$$

A precision-recall curve



Compare Two or More Systems

 The curve closest to the upper right-hand corner of the graph indicates the best performance



PRECISION@K

Precision@K

- Set a rank threshold K
- Compute % relevant in top K
- Ignores documents ranked lower than K
- Ex:
 - -Prec@3 of 2/3
 - -Prec@4 of 2/4
 - Prec@5 of 3/5

How to choose k for precision@k measure?

K传播教?

R-PRECISION

precison at R
recevent downert total

R- Precision

 Precision at the R-th position in the ranking of results for a query that has R relevant documents.

r	1	doc#	relevant
1		588	Х
2	2	589	Х
3	3	576	
4	1	590	Х
5	5	986	
6	3	592	X
7	7	984	
8	3	988	
ć)	578	
1	0	985	
1	1	103	
1	2	591	
1	3	772	X
1.	4	gan	

R = # of relevant docs = 6

R-Precision = 4/6 = 0.67

MEAN AVERAGE PRECISION



Mean Average Precision

Consider rank position of each relevant doc

$$- K_1, K_2, ... K_R$$

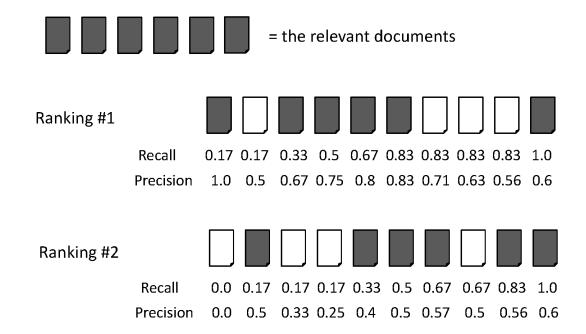
- Compute Precision@K for each K₁, K₂, ... K_R
- Average precision = average of P@K, for each K

• Ex:
$$\frac{1}{3} \times \left(\frac{1}{1} + \frac{2}{3} + \frac{3}{5}\right) \approx 0.76$$

MAP is Average Precision across multiple queries/rankings

$$MAP(Q) = \frac{1}{|Q|} \sum_{j=1}^{|Q|} \frac{1}{m_j} \sum_{k=1}^{m_j} Precision(R_{jk})$$

Mean Average Precision



Ranking #1: (1.0 + 0.67 + 0.75 + 0.8 + 0.83 + 0.6)/6 = 0.78

Ranking #2: (0.5 + 0.4 + 0.5 + 0.57 + 0.56 + 0.6)/6 = 0.52

MAP

mean average precision = (0.62 + 0.44)/2 = 0.53

When there's only 1 Relevant Document

- Scenarios:
 - known-item search
 - navigational queries
 - looking for a fact
- Search Length = Rank of the answer
 - measures a user's effort

Mean Reciprocal Rank RR

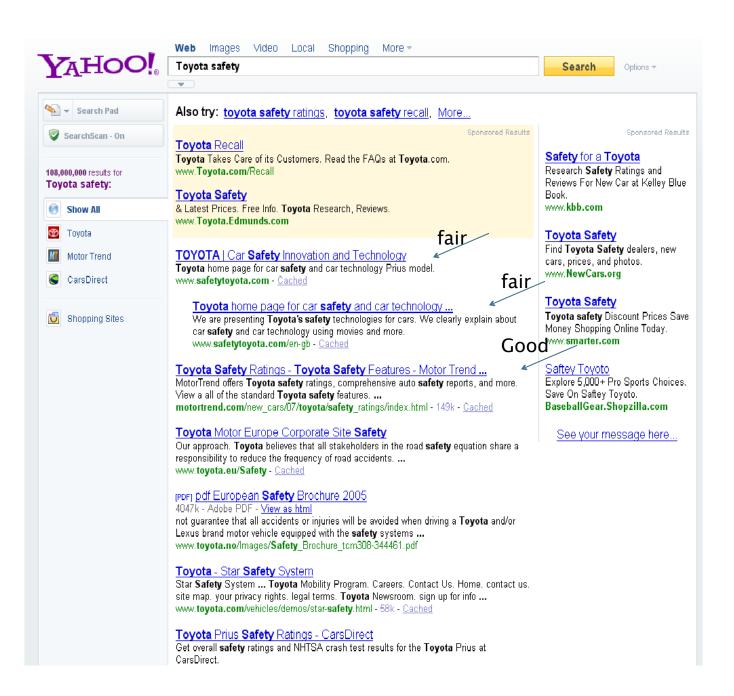
 Consider rank position, K, of first relevant doc 倒奴

• Reciprocal Rank Score =
$$\frac{1}{K}$$
 $\frac{1}{x-x-1}$

MRR is the mean RR across multiple queries

DISCOUNTED CUMULATIVE GAIN

本的是是多次第一 〇、1-2、3···· 權重值



Summarize a Ranking: DCG

- What if relevance judgments are in a scale of [0,r]? r>2
- Cumulative Gain (CG) at rank n

Let the ratings of the n documents be r_1 , r_2 , ... r_n (in ranked order)

 $-CG = r_1 + r_2 + ... r_n$

Discounted Cumulative Gain

 Popular measure for evaluating web search and related tasks

力的愈高致愈新面

- Two assumptions:
 - Highly relevant documents are more useful than marginally relevant document
 - the lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Discounted Cumulative Gain

- Uses graded relevance as a measure of usefulness, or gain, from examining a document
- Gain is accumulated starting at the top of the ranking and may be reduced, or discounted, at lower ranks
- Typical discount is 1/log (rank)
 - With base 2, the discount at rank 4 is 1/2, and at rank 8 it is 1/3

Discounted Cumulative Gain (DCG)

Discounted Cumulative Gain (DCG) at rank n

$$DCG = r_1 + r_2/\log_2 2 + r_3/\log_2 3 + ... r_n/\log_2 n$$

• We may use any base for the logarithm, e.g., base=b

排名包好被机方包少

DCG Example

- 10 ranked documents judged on 0-3 relevance scale:
 - -3, 2, 3, 0, 0, 1, 2, 2, 3, 0
- discounted gain:
 3, 2/1, 3/1.59, 0, 0, 1/2.59, 2/2.81, 2/3, 3/3.17, 0
 - = 3, 2, 1.89, 0, 0, 0.39, 0.71, 0.67, 0.95, 0
- DCG:
 - 3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61

希望0~/ 聞 NDCG

Discounted Cumulative Gain

 DCG is the total gain accumulated at a particular rank p:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}$$

Alternative formulation:

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log(1+i)}$$

- used by some web search companies
- emphasis on retrieving highly relevant documents

Summarize a Ranking: NDCG

正規化

- Normalized Cumulative Gain (NDCG) at rank n
 - Normalize DCG at rank n by the DCG value at rank n of the ideal ranking
 - The ideal ranking would first return the documents with the highest relevance level, then the next highest relevance level, etc
 - Compute the precision (at rank) where each (new) relevant document is retrieved => p(1),...,p(k), if we have k rel. docs
- NDCG is now quite popular in evaluating Web search

NDCG - Example

4 documents: d₁, d₂, d₃, d₄

	Ground Truth		Ranking Function ₁		Ranking Function ₂	
i	Document Order	r _i	Document Order	r _i	Document Order	r _i
1	d4	2	d3	2	d3	2
2	d3	2	d4	2	d2	1
3	d2	1	d2	1	d4	2
4	d1	0	d1	0	d1	0
	NDCG _G	_T =1.00	NDCG _{RF}	₁ =1.00	NDCG _{RF2}	=0.9203

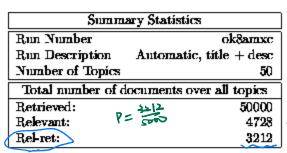
$$DCG_{GT} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$

$$DCG_{RF1} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$

$$DCG_{RF2} = 2 + \left(\frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.2619$$

$$MaxDCG = DCG_{GT} = 4.6309$$

Precion-Recall Curve



Out of 4728 rel docs. we've got 3212

Recall=3212/4728

e got 3212	us d
I=3212/4728	0.6
)docs	
about 5.5 docs in the top 10 docs are relevant	0.2 0.4 0.6 0.8 0.0 Recall-Precision Curve
	Kecan-Precision Cuive

Recall Level Precision Averages				
Recall	Precision			
/ 0.00	0.8190			
0.10 real	0.5975			
0.10 (early 0.20 precision 0.30 curve	0.5032			
0.30 CUTUR	0.4372			
0.40	0.3561			
0.50	0.2936			
0.60	0.2511			
0.70	0.1941			
0.80	0.1257			
0.90	0.0696			
V 1.00	0.0296			
Average precision over all				

relevant docs non-interpolated

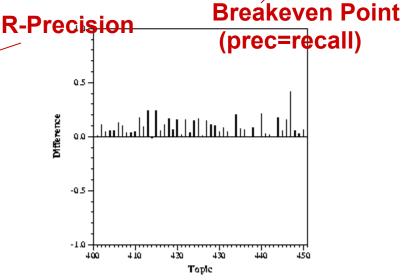
Precision	es
	10docs
At 5 docs 0.5800	<u></u>
At 10 does 0.5500	4
At 15 does 0.4987	about
At 20 does 0.4650	l in the
At 30 does 0.4253	are re
At 100 does 0.2680	alete
At 200 does 0.1921	
At 500 does 0.1085	
At 1000 does 0.0642	

R-Precision (precision after R docs retrieved (where R is the number of relevant documents))

0.3470Exact

Mean Avg. Precision (MAP)

0.3169



Difference from Median in Average Precision per Topic

Recap

- Precision, Recall, Accuracy
- Recall-Precision Curve
- Precision@k
- R-Precision
- MAP Measure
- NDCG Measure